Use of Alternative Depreciation Methods to Estimate Farm Tractor Values*

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Abstract

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Six depreciation methods were used to simulate the value of farm tractors with indexed and expected prices. Accuracy of simulated values was evaluated using paired t-tests of mean absolute percentage errors and forecast accuracy regression models. Results varied with age and use. Some depreciation methods were more accurate than others.

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Depreciation is the decrease in an asset's value over time because of age, wear, obsolescence, and changes in market conditions. An accurate estimate of farm machinery depreciation is necessary for farm management applications, such as crop enterprise selection, machinery services management, financial and tax planning, and analysis of herbicide/tillage tradeoffs. This study focused on tractor depreciation because tractors are used for a variety of production activities and are especially important on most crop farms.

Several studies provide alternatives for estimating the remaining value and annual depreciation of farm tractors. Each of these studies uses different calculation procedures and requires different information (e.g., Leatham and Baker; McNeill; Reid and Bradford; Hansen and Lee; Perry, Bayaner, and Nixon). In these studies, remaining value is the current market value (Perry, Bayaner, and Nixon) and annual depreciation is the change in remaining value from year to year. Thus, depreciation estimates result directly from market value estimates, and accurate market value predictions lead to accurate depreciation estimates. Alternative depreciation and valuation methods can be evaluated by comparing their accuracies for predicting market value. Dumler, Burton, and Kastens illustrated differences in predictive accuracy using a two-tractor example. However, the only study that evaluated predictive accuracy was the one by Hansen and Lee, who focused on 60 horsepower (hp) tractors and compared their depreciation method to U.S. and Canadian tax methods.

The objective of this study was to compare the accuracies of six different depreciation methods in predicting farm tractor values. This study differed from that of Hansen and Lee in the number of depreciation methods that were compared and consideration of tractors over 100 hp. The methods compared were those of the American Society of Agricultural Engineers (ASAE); Cross and Perry (CP); North American Equipment Dealers Association (NAEDA); and the Kansas Management, Analysis, and Research (KMAR) plus two U.S. income tax methods.

Depreciation Methods

Perhaps the most common method used to estimate depreciation and remaining value is the American Society of Agricultural Engineers (ASAE) method. It uses a geometric function in which remaining value percentage (RVP) is a function of age. The ASAE depreciation formula for tractors is

$$\text{RVP} = 0.68(0.92)^{n}, \quad (1)$$

where n is the age of tractors in years (American Society of Agricultural Engineers).

The second depreciation method examined in this study, referred to as CP, was developed by Cross and Perry in 1995. Their RVP, based on econometric estimates from auction data, is a function of age, usage, size, manufacturer, condition, region, auction type, and macroeconomic variables. Cross and Perry used a Box-Cox model to estimate RVP for machinery. This artificial scaling of data was used to better reflect the actual depreciation patterns inherent in different types of farm machinery (Unterschultz and Mumey). The general Box-Cox model is written as follows:

$$RVP = \left[(\beta_0 \lambda + 1) + \lambda \sum_i \beta_i \left(\frac{X_i^{\gamma_i} - 1}{\gamma_i} \right) + \lambda \sum_j \beta_j Z_j \right]^{-\lambda},$$

where RVP is the remaining value percentage of farm equipment, λ is the transformation on RVP, γ_i are the transformations on independent variables X_i, and Z_j represents all other independent variables not transformed. The transformed independent variables in their study were age and hours of use. For tractors, the data were divided into three horsepower classes: (1) 30-79 hp, (2) 80-150 hp, and (3) 150 and greater hp. Therefore, the study was able to determine differences in remaining value due to size (Cross and Perry).

The third method being compared was the North American Equipment Dealers Association (NAEDA) *Official Guide*. The NAEDA publishes a quarterly list of values for tractors and other farm equipment. These values are based on actual sales collected from farm equipment dealerships. Besides giving a base price for a tractor, the *Official Guide* allows users to adjust the value of a tractor according to the number of hours it has accumulated or the features it has (Wallace and Maloney).

The fourth depreciation procedure to be compared was the one used by the Kansas Farm Management Associations. This method is referred to as KMAR (Kansas Management, Analysis, and Research). The KMAR depreciation method uses a tax-like system to value equipment. Under this scenario, a different salvage value and time to reach that salvage value were assigned for each type of equipment by a committee of

Kansas Farm Management Association economists. Then, the tax-like depreciation method that most closely approximated the selected salvage value in the selected time frame was used to characterize the KMAR depreciation. For example, tractors were assigned a 35% salvage value in 10 years. The method of depreciation calculation that best arrived at that salvage value was a 100% 10-year declining balance method (Kastens).

For comparison, two methods of calculating depreciation for tax purposes were included in this study to determine how tax depreciation related to actual economic depreciation. The two Modified Accelerated Cost Recovery (MACRS) tax methods used for comparison were the 150% Declining Balance with the General Depreciation System (GDS) recovery period and the Straight Line with the Alternative Depreciation System (ADS) recovery period (U.S. Dept. of the Treasury). Based on U.S. income tax policy, the first of these two methods takes the most depreciation allowed earliest in a tractor's useful life, and the second takes the most depreciation allowed latest in a tractor's useful life.

Although other methods for estimating annual depreciation and remaining value exist (e.g., Hansen and Lee, Unterschultz and Mumey), the six methods considered provided a range of simplicity and complexity. They also provided a variety of procedures for estimating depreciation and remaining value such as econometric models based on theory, expert opinion, income tax laws, and comparable sales. Additional information about the six methods is available in Dumler.

Methodology and Data

The methodology used to compare tractor valuation accuracy across the six depreciation methods involved two price scenarios, two data sets, and two analytical procedures. A current list price was required for several of the tractor valuation methods. The two price scenarios used to obtain a current list price were based on current (year sold) indexed values, and expected (future) values. The two data sets covered a long-term time period (1986-August 1995) and a short-term time period (January - August 1995). The two analytical procedures were pairwise comparisons of mean absolute percentage error (MAPE) and forecast accuracy regression models. The scenarios and data sets were used to specify three models to which both analytical procedures were applied: indexed prices with 1986-1995 data, indexed prices with 1995 data, and expected prices with 1986-1995 data.

Indexed Prices Scenario

The indexed prices scenario focused on the current value of tractors in the year sold. This scenario used known tractor price index values, along with purchase or list prices when new, to develop estimates of the current list prices required for the formulas underlying the various depreciation methods. The depreciation formulas were then used to predict tractor selling prices (P), which, when subtracted from actual selling prices (A), yielded prediction errors (A-P). The list or purchase prices were indexed using the 110-129 hp tractor price index from *Agricultural Prices* (USDA, National Agricultural Statistics Service). Because indexed tractor prices were assumed to be known, this was effectively an in-sample prediction exercise. At the time this study was initiated, a tractor price data set for 1986 through 1995 was available in a useable form. Because it was the first year when NAEDA published their price guides in a new format, the NAEDA method could be applied only to the 1995 data. Therefore, two data sets were examined using the indexed tractor values: tractors sold between 1986-95 and those sold in 1995. These models are referred to as *indexed prices with 1986-95 data* and *indexed prices with 1995 data*.

Expected Prices Scenario

The third scenario used a naive expectation of inflation based on Producer Price Index (PPI) values, along with purchase or list prices when new, to effectively make "out-of-sample" or future price predictions. Only the 1986-95 data set was used with this scenario, because the NAEDA method could not be used to predict the future values of tractors. This model is referred to as *expected prices with 1986-95 data*. The procedures used to predict future tractor values were identical to those used to predict current tractor values, except that the list prices for the individual tractors were calculated on the basis of an expected tractor price inflation rate, because this information would be unknown in real-time prediction.

Data

Monthly sale prices for tractors from 1986 through August 1995 were obtained from the *Farm Equipment Guide* published monthly by Hot Line, Inc. This study isolated those tractors over 100 hp produced from 1975 to 1995 by the major farm equipment manufacturers, including John Deere (JD), Case-IH, International (IH), Ford, Allis, Massey Ferguson (MF), and White. The final data set contained 7,272 observations. In addition to these data, net farm income values, prime interest rates, and current list and purchase prices were needed to complete the analysis of the depreciation methods. Sources of these additional data were *Agricultural Outlook* (USDA, Economic Research Service); the Federal Reserve Bank; and the NAEDA *Official Guide* for 1975-94. The net farm income values, prime interest rates, and current list prices were needed to use the CP method. Current list prices also were needed for the ASAE method, whereas initial purchase prices were needed for the KMAR, GDS, and ADS methods.

Pairwise Comparisons of Mean Absolute Percentage Error

Two procedures were used to compare the accuracy of the six depreciation methods. The first procedure used the forecast accuracy test statistic, absolute percentage error (APE):

$$APE = |(A - P)/A| * 100 \, , \qquad (3)$$

where P is the predicted remaining value, A is the actual remaining value, and A-P is the forecast error. Determining which method was the most accurate was accomplished through paired-*t* tests in pairwise comparisons of mean absolute percentage error (MAPE). Methods with the lowest MAPEs are the most accurate.

Forecast Accuracy Regression Models

The second depreciation evaluation procedure involved use of forecast accuracy regression models to aid accuracy generalization across models and model features. In these models, APE was assumed to be a function of age, year of sale, annual hours of use, size, manufacturer, and depreciation method:

$$APE_{ijt} = \beta_0 + \beta_1 AGE + \beta_2 AGE^2 + \beta_3 YR + \beta_4 YR^2 + \beta_5 HP + \beta_6 ALLIS + \beta_7 CASE\text{-}IH + \beta_8 IH + \beta_9 FORD + \beta_{10} MF + \beta_{11} WHITE + \beta_{12} ASAE + \beta_{13} CP + \beta_{14} NAEDA + \beta_{15} GDS + \beta_{16} ADS + \beta_{17} AGE{*}ASAE + \beta_{18} AGE{*}CP + \beta_{19} AGE{*}NAEDA + \beta_{20} AGE{*}GDS + \beta_{21} AGE{*}ADS + \beta_{22} AGE^2{*}ASAE + \beta_{23} AGE^2{*}CP + \beta_{24} AGE^2{*}NAEDA + \beta_{25} AGE^2{*}GDS + \beta_{26} AGE^2{*}ADS + \beta_{27} HPY{*}CP + \beta_{28} HPY{*}NAEDA + \beta_{29} HPY^2{*}CP + \beta_{30} HPY^2{*}NAEDA. \quad (4)$$

In (4), APE_{ijt} is the absolute percentage error associated with using depreciation method *i* to predict the value for tractor *j* that was sold in year *t*, AGE is the age for used tractor *j* in year *t*, YR is the year the tractor was sold, and HPY is the hours per year the tractor has been used since new (accumulated hours/age). HP is a binary variable equal to 1 if the tractor is larger than 150 hp or else 0. ALLIS, CASE-IH, IH, FORD, MF, and WHITE are dummy variables corresponding to each of the tractor manufacturers (JD was the default manufacturer). ASAE, CP, NAEDA, GDS, and ADS are dummy variables corresponding to each of the depreciation methods (KMAR was the default). The squared AGE, YR, and HPY terms consider that APEs may be nonlinear. From the AGE and HPY interaction terms, it can be determined which method estimates tractor value more accurately as a tractor ages or is used more intensively. The HPY interaction terms are used only with the CP and NAEDA methods, because they are the only methods in which HPY is a variable that determines remaining value.

Buyers, sellers, and financiers of farm tractors may be especially interested in how age and use affect market values. Impacts of individual variables can be measured and visualized using the APE regression equations by inserting the mean values of all independent variables except for one and then varying the one variable, solving for APE, and graphing the results. This procedure was used to provide graphical information about how APE varies with age and annual average hours of use (HPY).

Results and Discussion

The two analytical procedures used to evaluate the accuracy of remaining value forecasts of the six depreciation methods were pairwise comparisons of MAPEs and regression models.

Pairwise Comparisons of MAPEs

The CP method had the lowest MAPEs (ranging from 25.7 to 42.5) in all testing scenarios (Table 1). After the CP method, the ASAE, NAEDA, and KMAR methods ranked lowest to highest with respect to MAPE. The ADS and GDS tax methods had the highest MAPEs, ranging from 61.2 to 82.8 and 80.8 to 90.9, respectively. Thus, the two tax methods likely would be poor predictors of farm tractor market value.

The CP method had a statistically lower MAPE than the other depreciation methods (Table 2). Therefore, it was, on average, the most accurate. Following the CP method, the ASAE method had a statistically lower MAPE than the other four methods. The indexed prices model with 1995 data, where the difference between accuracies of ASAE and NAEDA could not be distinguished, was an exception. The NAEDA method was the next most accurate. On an individual basis, it was statistically more accurate than KMAR, ADS, and GDS methods, in relative order of accuracy.

Regression Models

Equation 4 was estimated (ordinary least squares) independently for each of the three models. Like the paired-*t* tests, two models were estimated using indexed list and purchase prices, and one model was estimated using expected list and purchase prices (a unique regression model corresponds to the data represented by each column in Table 1). The three forecast accuracy regression models provided a more in-depth picture of each depreciation method's accuracy.

Table 3 shows the estimated coefficients and *t* statistics associated with the indexed and expected price models. KMAR was the default in each model, because in terms of MAPE, it was intermediate to the other methods. JD was chosen as the default manufacturer dummy variable because 52% of the tractors in the data set were JD. In the regression models, accuracy is seen as a complex combination of continuous variables, dummy variables, and interactions. As a result, it is difficult to interpret the marginal impacts associated with each variable.

To better visualize Table 3 results, several figures were constructed with regression model predictions that focused on prediction accuracy with respect to age and hours of use. For example, Figure 1 was constructed by inserting the mean values of all variables except for AGE into the corresponding regression equation and solving for APE. Then AGE was allowed to vary from 0 to 20. Graphs for tractor manufacturers other than

JD were similar (Dumler pp. 93-98).

Indexed Prices with 1986-1995 Data. Figures 1 and 2 illustrate how APE for JD tractors changed as age and hours of use per year increase. For tractors under 10 years of age, the KMAR, ASAE, and CP methods were relatively consistent in predicting the value of JD tractors. However, after 10 years, only the ASAE and CP methods remained consistent. The KMAR method became increasingly inaccurate after 10 years, because RVP remains constant at 35% of the initial purchase price beyond 10 years. The ASAE and CP methods, conversely, consider age as a variable that determines remaining value. Consequently, although these two methods became less accurate over time, they did so at a much less rapid pace than the KMAR method. On the opposite end, the GDS method became more accurate after 13 years, while the ADS method leveled off after 19 years. This occurred because the predicted RVP is zero after years 8 and 11 for the GDS and ADS methods, respectively. Thus, APE decreased as tractors aged and actual RVP moved closer to zero.

The relationship between APE and use, measured as HPY and depicted in Figure 2, was different than that between APE and AGE. The primary reason that a difference occurred between AGE and HPY in relation to APE was that only the CP method considered HPY as a variable in determining remaining value. The other methods have constant remaining values across different levels of use. Thus, only interaction terms between HPY and CP and HPY^2 and CP were used in the model. Also, instead of HPY being held constant at its mean, AGE was held constant at its mean of 9.1 years. Figure 2 shows that varying HPY from 0 to 800 resulted in more linear relationships than varying AGE. The CP method had the lowest APE across most levels of use. This was expected to occur because of the use of HPY as a variable in the CP remaining value equation. However, the KMAR method had a lower APE after around 625 HPY, whereas the ASAE method had a lower APE after around 750 HPY. Consequently, though the KMAR and ASAE methods had constant APE values across all levels of use, they were more accurate predictors of remaining value for tractors used more than 625 HPY and 750 HPY, respectively. The CP method, conversely, was most accurate for tractors used less than 625 HPY. Like the KMAR and ASAE methods, the ADS and GDS tax methods were constant across all levels of use, but were inaccurate relative to the other methods.

Indexed Prices with 1995 Data. The regression model with 1995 Indexed Prices was structured differently than the 1986-95 model (Table 3). Namely, the YR and YR^2 variables were excluded, because they were not relevant. Also, interaction terms between HPY and NAEDA and HPY^2 and NAEDA were added, because the remaining value of tractors computed by the NAEDA method varied with intensity of use. When APE was graphed in relation to AGE, with all other variables held constant, the results were somewhat surprising (Figure 3). Unlike the previous model with 10 years of data, four of the six depreciation methods had low APEs for tractors 0 to 2 years old, i.e., the KMAR, ASAE, CP, and NAEDA methods. From years 3 to 9, the NAEDA method had the lowest APE, even though it had the third lowest MAPE (Table 1). After 9 years, the CP method had the lowest APE, that diminished after year 12.

As with the 1986-95 data, tractors over 150 hp had larger APEs (see the HP coefficient in the Indexed Prices 1995 column of Table 3). For this model, the APE of a tractor over 150 hp was 6 percentage points larger than the APE for a tractor under 150 hp.

Figure 4 illustrates the relationship between APE and HPY, holding all other variables constant. Across all levels of use, the CP method had the lowest APE and, therefore was the most accurate. The NAEDA method initially had the fourth highest APE, but it decreased until 475 HPY, whereupon it began to increase again. For tractors used 175 to 725 HPY, NAEDA had the second lowest APE. Both the ASAE and KMAR methods were more accurate than the NAEDA method for tractors used less than 175 and 125 HPY and more than 725 and 775 HPY, respectively. In this model, the ASAE method had a lower APE than the KMAR method, which was the opposite of what occurred in the model with 10 years of data. As in the other models, the APE values of ADS and GDS were generally much higher than the APE values of the other methods.

Expected Prices with 1986-1995 Data. Perhaps the greatest potential use of the alternative depreciation methods is to forecast the future value of farm tractors. The third model displayed in Table 3 estimated the accuracy of predicting the future value of farm tractors over the entire data set using all but the NAEDA depreciation method. The difference between this model and the others is that the list and purchase prices in the depreciation formulas used to calculate remaining value are based on an expected inflation rate rather than a known rate. Nonetheless, if an example tractor is taken in the year it was manufactured with the assumption it will be held until the year of sale provided in the data, these depreciation methods can be used to calculate the future value of that tractor in the year it was sold.

Several observations can be made from the regression results of this model (Table 3). First, the R^2 computed using the expected prices model was 0.1025 versus 0.1588 for the comparable model using indexed prices. This is not surprising, because the prices used to compute remaining values were based on predicted inflation rather than actual inflation. Therefore, the model based on expected prices did not fit as well as the model based on indexed prices. The YR and YR^2 variables were significant in the expected prices model, whereas they were not in the indexed prices model. This indicates that APE was affected by the year a tractor was sold. In addition, the depreciation methods were more inaccurate for predicting the remaining value of tractors larger than 150 hp. The APEs for tractors over 150 hp were 9.5 percentage points higher than the APEs for tractors under 150 hp.

Some dramatic differences also occur between the expected prices model and the indexed prices model in terms of the relationship between APE and AGE. In the first model (Figure 1), the inaccuracy of ASAE and CP increased over time. In the expected prices model (Figure 5), APE for the CP and ASAE methods increased until year 11 or 12 and then decreased. Also, instead of increasing rapidly, the KMAR APE began to decrease after 17 years. The two tax methods followed the same general patterns as before.

Considering only the two most accurate methods, ASAE and CP, the results were promising yet disappointing. They were promising in that the APEs decreased for tractors over 11 years old, but they were highest for tractors around 10 years of age, when many farmers replace their tractors. (In our data the average age of the tractors when sold was 9 years). In spite of this minor disappointment, it was encouraging to discover that the ASAE and CP methods performed almost as well when forecasting future tractor values as they did when forecasting current tractor values.

Similar to the APE-AGE relationship, the APE-HPY relationship was interesting for the expected prices model (Figure 6). In this model, the CP APE increased more rapidly than it did in the indexed prices model with 1986-95 data. Thus, it was higher than APE for the ASAE method after 325 HPY. Then, after 575 HPY, KMAR had a lower APE than the CP method. The other interesting result was that the ADS tax method was as accurate at 800 HPY as the CP method.

Suggestions for Future Research

Although this study shed new light on the accuracy of six alternative depreciation methods, further study certainly is merited. First, it would be helpful to have a data set that provides more information on each tractor. For instance, it would be useful to know more features about each tractor, such as whether it had mechanical front wheel drive (MFWD). The accuracy of the NAEDA method may have been diminished by this lack of information. Second, this type of research can be applied to other classes of farm machinery such as harvest, haying, tillage, and planting equipment. Finally, future research could consider other depreciation methods.

Conclusions

Although much literature exists on farm tractor depreciation, little is known about the accuracy of different depreciation methods. This study compared a variety of methods that considered different factors for estimating depreciation and varied in difficulty of use. It focused on tractors, the primary machines used on most crop farms. Overall, the Cross and Perry depreciation method had the lowest mean absolute percentage error and therefore was generally the most accurate. However, the North American Equipment Dealers Association method was the most accurate when 1995 indexed prices were used for estimating the current value of tractors 3 to 9 years of age, and the American Society of Agricultural Engineers method was nearly as accurate as the Cross and Perry method for estimating the future value of tractors. Because no method is consistently the most accurate, farm managers must devote significant time and thought to choosing a depreciation method for their farm businesses.

References

American Society of Agricultural Engineers. *ASAE Standards*. 43rd ed. St. Joseph, MI., 1996.

Cross, T.L. and G.M. Perry. "Depreciation Patterns for Agricultural Machinery." *American Journal of Agricultural Economics.* 77(Feb., 1995): 194-204.

Dumler, Troy J. "Predicting Farm Tractor Values through Alternative Depreciation Methods." MS thesis, Kansas State University, 1998.

Dumler, T. J., R. O. Burton, Jr., and T. L. Kastens. "Implications of Alternative Farm Tractor Depreciation Methods." Selected paper at the AAEA annual meeting, Salt Lake City, Utah, August 2-5, 1998.

Federal Reserve Bank. Dec. 1997. <http://www.bog.frb.fed.us/releases/h15/data/a/prime.txt>.

Hansen, L. and H. Lee. "Estimating Farm Tractor Depreciation: Tax Implications." *Canadian Journal of Agricultural Economics.* 39(Nov., 1991): 463-479.

Hot Line, Inc., *Hot Line: Farm Equipment Guide.* Fort Dodge, Iowa., various dates.

Kastens, T.L. "Machinery Costs: Selected Topics." Paper presented at School of Rural Banking, Wichita, Kansas, 4 June 1997.

Leatham, D.J. and T.G. Baker. "Empirical Estimates of the Effects of Inflation on Salvage Value, Cost, and Optimal Replacement of Tractors and Combines." *North Central Journal of Agricultural Economics* 3(July, 1981): 109-117.

McNeill, R.C. "Depreciation of Farm Tractors in British Columbia." *Canadian Journal of Agricultural Economics* 27(Feb., 1979): 53-58.

Perry, Gregory M., Ahmet Bayaner, and Clair J. Nixon. "The Effect of Usage and Size on Tractor Depreciation." *American Journal of Agricultural Economics.* 72(May, 1990): 317-325.

Reid, D.W., and G.L. Bradford. "On Optimal Replacement of Farm Tractors." *American Journal of Agricultural Economics.* 65(May, 1983): 326-331.

Unterschultz, J. and G. Mumey. "Reducing Investment Risk in Tractors and Combines with Improved Terminal Asset Value Forecasts." *Canadian Journal of*

Agricultural Economics. 44(Nov., 1996): 295-309.

U.S. Department of Agriculture, National Agricultural Statistics Service. *Agricultural Prices*. Washington DC, various dates.

U.S. Department of Agriculture, Economic Research Service. *Agricultural Outlook.* Washington DC, 1998.

U.S. Department of the Treasury, Internal Revenue Service. *1999 Farmer's Tax Guide.* Washington DC, 1999.

Wallace, J.A. and J.R. Maloney, eds. *Guides2000: Northwest Region Official Guide.* North American Equipment Dealers Association. St. Louis, MO. September, 1997.

Table 1. Mean Absolute Percentage Errors under Different Testing Scenarios

Depreciation Method[a]	Indexed Prices[b] (1986-95)	Indexed Prices[b] (1995)	Expected Prices[c] (1986-95)
ASAE	37.2	38.7	44.9
CP	31.4	25.7	42.5
NAEDA	–	41.5	--
KMAR	43.7	52.5	54.9
GDS	82.9	90.9	80.8
ADS	65.2	82.8	61.2
Average	52.1	55.4	56.8

[a] Abbreviations for depreciation methods are as follows: ASAE = American Society of Agricultural Engineers; CP = Cross and Perry; NAEDA = North American Equipment Dealers Association; KMAR = Kansas Management, Analysis, and Research; GDS = Method used for U.S. income taxes under the Modified Accelerated Cost Recovery System (MACRS) that uses 150% declining balance calculations and the General Depreciation System (GDS) recovery period; and ADS = Method used for U.S. income taxes under MACRS that uses straight line calculations and the Alternative Depreciation System (ADS) recovery period.

[b] Indexed prices scenarios used known tractor price index values, along with purchase or list prices when new, to develop estimates of the current (year of sale) list and purchase prices required of the formulas underlying the various depreciation methods to predict current (year of sale) tractor values.

[c] The expected prices scenario used a naive expectation of inflation (based on the PPI), along with purchase or list prices when new, to develop expected future (expected year

of sale) list and purchase prices required of the formula underlying the various depreciation methods to predict future tractor values.

Table 2. t Statistics of Pairwise Comparisons of Mean Absolute Percentage Errors[a]

	ASAE	CP	GDS	ADS	NAEDA
Indexed Prices (1986-95)					
KMAR	10.8*	14.2*	-30.5*	-17.5*	--
ASAE		11.8*	-54.4*	-35.0*	--
CP			-64.0*	-44.0*	--
GDS				49.9*	--
Indexed Prices (1995)					
KMAR	4.2*	8.1*	-9.4*	-7.3*	4.2*
ASAE		7.4*	-21.8*	-16.2*	-1.0
CP			-29.7*	-21.0*	-6.3*
GDS				7.5*	15.1*
ADS					12.0*
Expected Prices (1986-95)					
KMAR	18.1*	14.0*	-17.2*	-4.5*	--
ASAE		4.1*	-31.3*	-15.4*	--
CP			-35.0*	-18.4*	--
GDS				41.5*	–

[a] Abbreviations for depreciation methods are as follows: ASAE = American Society of Agricultural Engineers; CP = Cross and Perry; NAEDA = North American Equipment Dealers Association; KMAR = Kansas Management, Analysis, and Research; GDS = Method used for U.S. income taxes under the Modified Accelerated Cost Recovery System (MACRS) that uses 150% declining balance calculations and the General Depreciation System (GDS) recovery period; and ADS = Method used for U.S. income taxes under MACRS that uses straight line calculations and the Alternative Depreciation System (ADS) recovery period. The numbers presented in this table are the *t* statistics of the paired-*t* tests. A positive *t* statistic indicates that the depreciation method across the top has a lower MAPE and, therefore, is more accurate. A negative *t* statistic indicates

that the depreciation method along the side is more accurate.

*Indicates two-tail significance at 0.05 level.

Table 3. Forecast Accuracy Regression Results

Variables[a]	Indexed Prices (1986-95)		Indexed Prices (1995)		Expected Prices (1986-95)	
	Estimated Coefficient	*t* Statistic	Estimated Coefficient	*t* Statistic	Estimated Coefficient	*t* Statistic
AGE	-2.8114	-3.790*	1.8039	0.8115	9.4501	10.33*
AGE^2	0.4168	10.93*	0.0881	0.9234	-0.2841	-5.820*
YR	3.8809	0.3471	--	--	-104.82	-7.418*
YR^2	-0.0152	-0.2451	--	--	0.6021	7.680*
HP	4.9614	6.763*	6.0923	2.865*	9.4528	9.831*
ALLIS	-1.2256	-0.7204	43.397	7.232*	12.588	6.419*
CASE-IH	3.9167	3.855*	16.041	5.790*	8.1799	7.032*
IH	3.0723	3.084*	16.416	6.277*	12.992	11.07*
FORD	-3.9956	-2.208*	1.0911	0.1790	0.2555	0.1777
MF	10.451	4.645*	22.281	2.834*	25.304	9.612*
WHITE	0.7583	0.2886	1.0077	0.1434	7.0993	2.718*
ASAE	-6.4011	-1.391	-12.719	-0.7658	7.8643	1.868
CP	-14.086	-2.781*	-0.5978	-0.0323	-19.117	0.1098
NAEDA	–	–	9.7403	0.5256	--	--
GDS	-38.474	-8.362*	-10.839	-0.6526	-14.363	1.133
ADS	-49.056	-10.66*	-51.805	-3.119*	-13.844	0.8725
AGEASAE	4.9130	4.738*	6.0191	1.921	-0.8368	-0.7236
AGECP	3.9202	3.770*	1.2598	0.4009	2.1785	1.405
AGENAEDA	--	--	1.4566	0.0636	--	--
AGEGDS	21.169	20.41*	12.190	3.890*	10.415	7.678*
AGEADS	16.425	15.84*	15.066	4.808*	2.6050	1.773
AGE^2ASAE	-0.4400	-8.341*	-0.4062	-3.021*	-0.0999	-1.483
AGE^2CP	-0.3978	-7.528*	-0.2175	-1.608	-0.2499	-3.736*
AGE^2NAEDA	--	--	-0.1101	-0.8142	--	--
AGE^2GDS	-1.1332	-21.48*	-0.5622	-4.182*	-0.5373	-8.067*
AGE^2ADS	-0.7782	-14.75*	-0.5879	-4.373*	-0.0356	-0.5364
HPYCP	-0.0221	3.325*	-0.0168	-0.3941	-0.0407	-1.329
HPYNAEDA	--	--	0.0000403	0.9141	--	--
HPY^2CP	0.000005	-1.522	-0.1059	-2.486*	0.0000082	0.6800
HPY^2NAEDA	--	--	0.0001206	2.738*	--	--
Constant	-203.16	--	1.0878	--	4540.1	--
R^2	0.1588	--	0.4240	--	0.1025	--

[a] APE is the dependent variable.

*Indicates significance at 0.05 level.

Figure 1. Model-Predicted Absolute Percentage Errors of John Deere Tractors across Different Ages with Indexed Prices (1986-95)

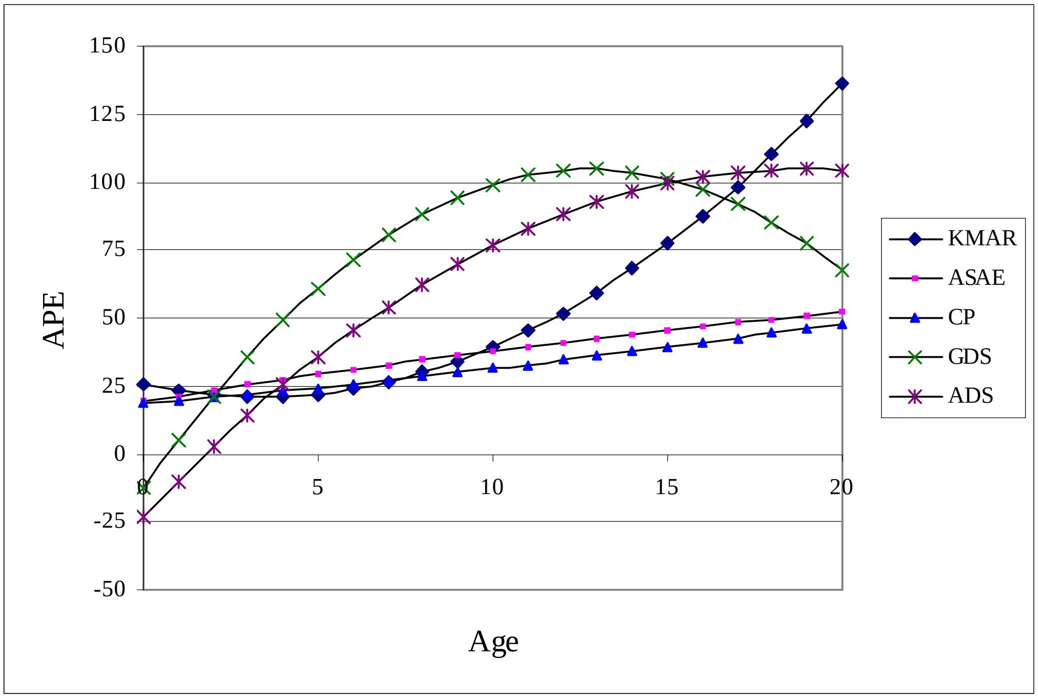

Figure 2. Model-Predicted Absolute Percentage Errors of John Deere Tractors across Different Levels of Use with Indexed Prices (1986-95)

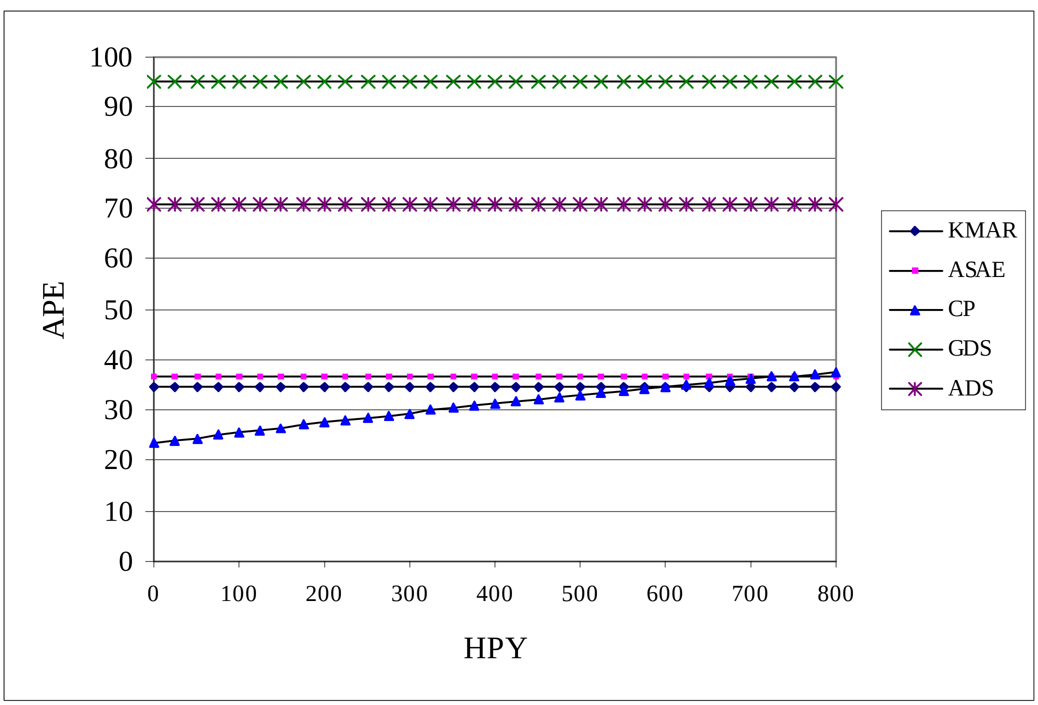

Figure 3. Model-Predicted Absolute Percentage Errors of John Deere Tractors across Different Ages with Indexed Prices (1995)

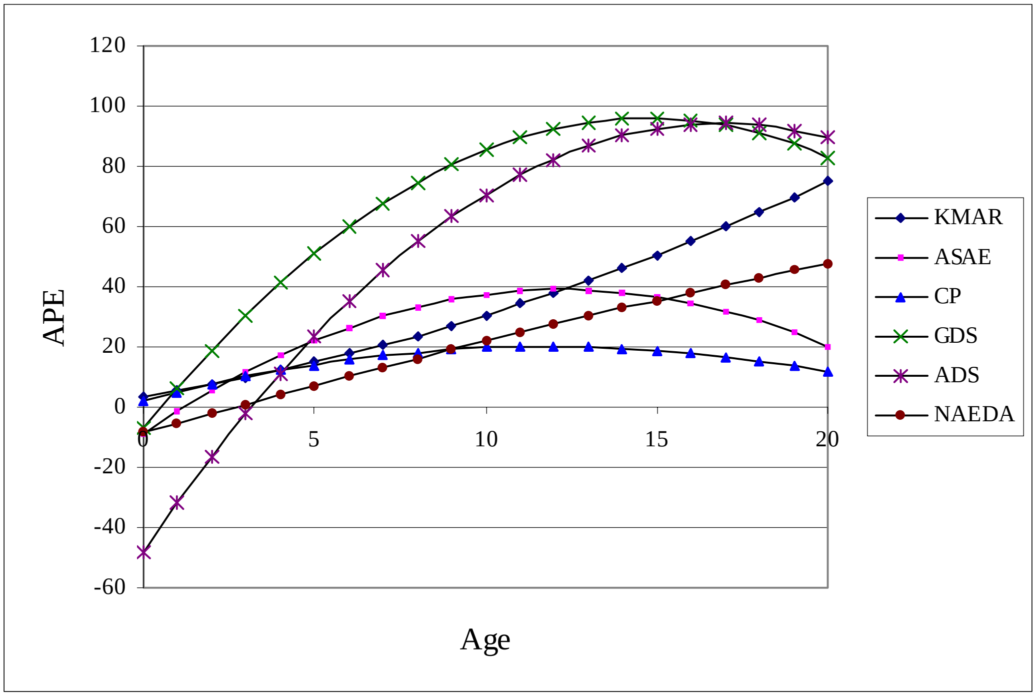

Figure 4. Model-Predicted Absolute Percentage Errors of John Deere Tractors across Different Levels of Use with Indexed Prices (1995)

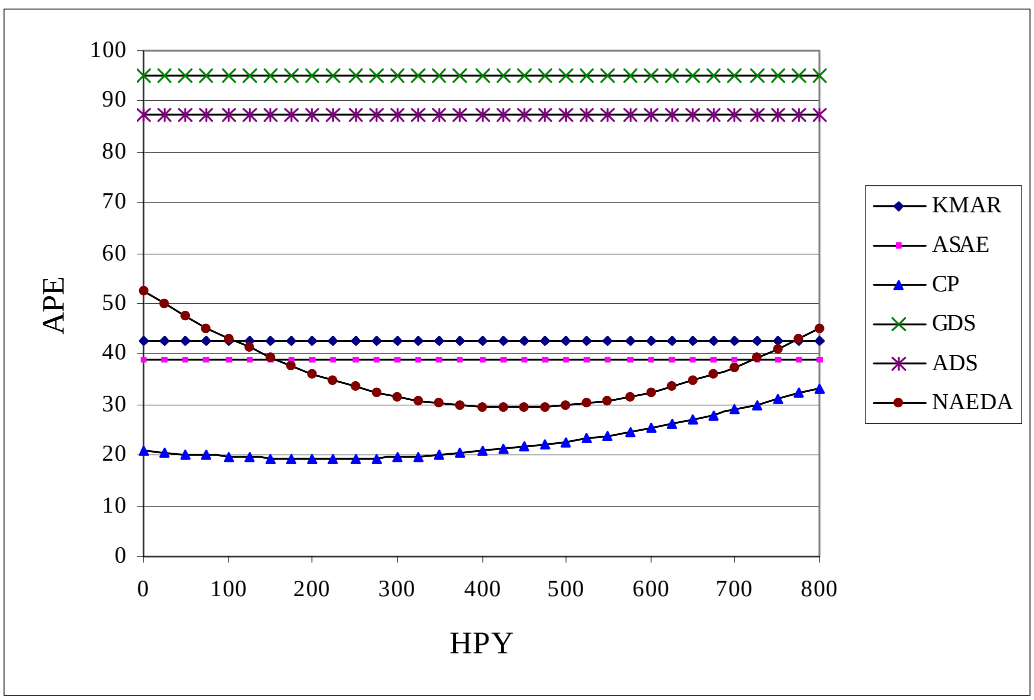

Figure 5. Model-Predicted Absolute Percentage Errors of John Deere Tractors across Different Ages with Expected Prices (1986-95)

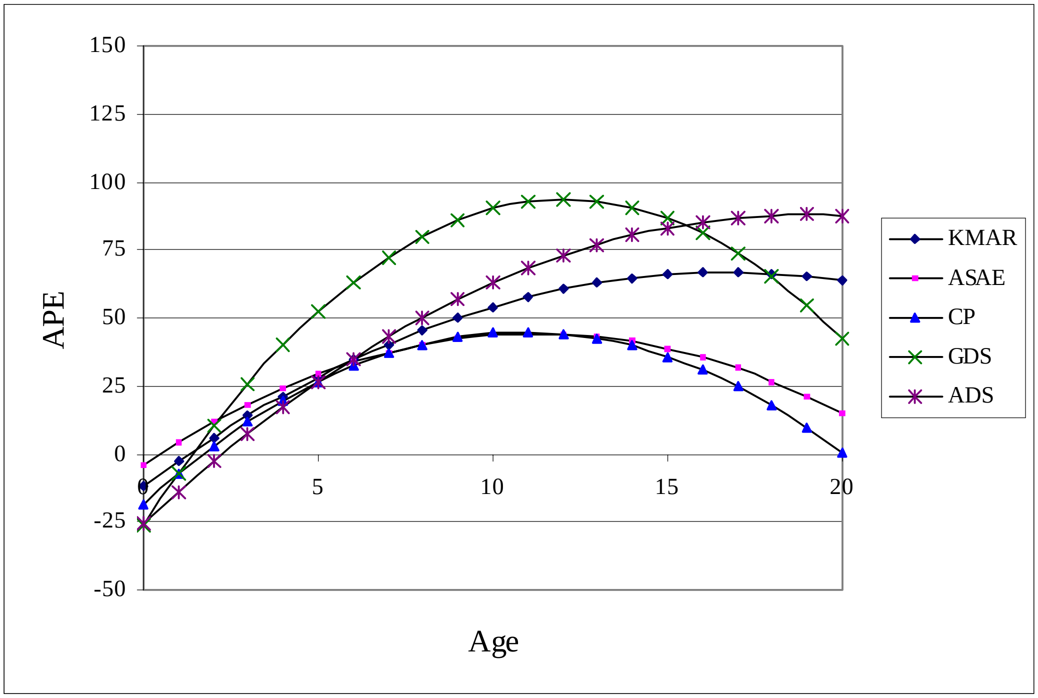

Figure 6. Model-Predicted Absolute Percentage Errors of John Deere Tractors across Different Levels of Use with Expected Prices (1986-95)